

# Do technical improvements lead to real efficiency gains? Disaggregating changes in transport energy intensity

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## Abstract

Fuel economy standards are a key measure to increase the rate of efficiency improvements in passenger cars. The fuel consumption of vehicles can be improved in three ways: incremental technical efficiency improvements within powertrain technologies, market shifts to more efficient types of powertrains and by limiting increases in the size and performance of vehicles. This study quantifies the effect of each of these three drivers on the fuel consumption of British vehicles between 2001 and 2018 using driver-reported data on real-world fuel consumption. Analysis shows the introduction of EU fuel economy standards in 2008/09 had little effect on the rate of real technical efficiency improvements in British vehicles. Instead of adopting technical improvements at a higher rate or limiting the size and power of vehicles, these results suggest vehicle manufacturers met emissions standards by increasing the divergence between laboratory tests and real-world fuel consumption. This study adds to the growing literature calling for official test procedures to be representative of real-world driving.

## 1 Introduction

Reducing the demand for energy is key to reaching current climate targets [1]. According to the International Energy Agency [2], the transportation sector has the highest potential for cost efficient energy intensity improvements of all sectors in the energy system, yet global emissions in the sector continue to increase due to both growing demand and the slow rate of energy intensity improvements [3]. Numerous governments around the world have imposed fuel economy standards on light duty passenger vehicles in efforts to increase the rate of efficiency improvements [4]. Measuring the impacts of these policies on vehicle efficiency is essential to ensure their effectiveness.

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Fuel economy standards set targets for type-approval (tested) vehicle CO<sub>2</sub> emissions (gCO<sub>2</sub>/km) or fuel consumption (L/100km or mpg) in order to track progress in energy efficiency. However, these measures are only a partial way to quantify real engineering efficiency improvements in vehicles, for two distinct reasons.

Firstly, potential energy savings from technical efficiency improvements (such as improved combustion, lubrication, transmission) can be offset by vehicle attributes that are detrimental to vehicle fuel economy, such as increasing vehicle size and power. By solely tracking improvements in gCO<sub>2</sub>/km or L/100km, it is challenging to estimate the technical efficiency improvements deployed over the time period of study, as they may have been masked by other vehicle attributes.

Secondly, testing procedures used to determine type-approval fuel consumption have been shown to be unrepresentative of real-world driving, particularly in the EU and other countries using the ‘New European Drive Cycle’ (NEDC) [5,6]. This means that apparent efficiency improvements in testing may not materialise under real-world driving conditions.

Quantifying real technical efficiency improvements, and the lost potential energy savings due to increasing vehicle size and power, can help policy-makers measure the effectiveness of past policies and ensure future targets maximise reductions in fuel consumption.

## 2 Literature Review

Several authors have sought to decompose changes in fuel consumption into technical efficiency improvements and the impact of changes in vehicle attributes. Technical efficiency improvements (TEI) can be quantified in terms of the hypothetical fuel consumption that vehicles could have attained had vehicle attributes remained constant from a past year. The difference between this hypothetical fuel consumption and the real observed trend can be thought of as the effect that changes in vehicle attributes had on fuel consumption. This approach uses regression models, similar to equation 1, to explain the variance in fuel consumption of vehicles each year using a selection of vehicle attributes. Year fixed effects are used to quantify annual improvements in fuel consumption, independent of vehicle attributes such as size and power.

$$\ln(FC)_{it} = T_t + \beta \ln(X_{it}) + \epsilon_{it} \quad (1)$$

Where  $FC$  is the observed fuel consumption of vehicle  $i$  in year  $t$ ,  $T$  are year fixed effects/dummy variables which take the value of 1 in year  $t$  and 0 otherwise,  $X$  is a vector of vehicle attributes such as power, size or weight,  $\beta$  is a vector of their respective regression coefficients and  $\epsilon$  is an error term.

Some of the first authors to use this technique were *Sorrell* [7] and *Kwon et al.* [8] who aimed to quantify technical efficiency improvements in the UK market between 1983-90 and 1978-2000 respectively. However, data limitations at the time meant that only the effect of engine capacity could be assessed. *Knittel*

[9] and *Mackenzie & Heywood* [10] later investigated technical improvements in passenger cars in the USA using a larger number of vehicle attributes. Together they showed that during times of high oil price, the rates of TEI increased and size and power increases slowed.

Fuel economy standards may also stimulate increasing rates of technical efficiency improvements. *Hu & Chen* [11] and *Klier & Linn* [12] studied the EU market between 1975-2015 and 2005-2010 respectively and reported higher rates of TEI after the introduction of binding EU emissions standards in 2008/09.

Some past studies [9–11] focussed on comparing the hypothetical fuel consumption had all vehicle attributes remained constant, to the average fuel consumption of available models. This neglects the effect of shifts in vehicle sales. If the type of vehicles on the market remains similar, but vehicle sales shift to larger cars (as has been the case in almost all countries [4]), increases in vehicle attributes will have been considerably more than the average of vehicles available for sale might indicate.

*Matas et al.* [13] applied similar methods to the Spanish vehicle market between 1988-2013 and sales-weighted results. Other notable improvements include adequately treating petrol and diesel vehicles separately. If two different technologies have different regression coefficients, then grouping them together in one regression can lead to a misleading model. It also makes it impossible to distinguish between technical improvements within technologies and shifts in sales to more efficient powertrain technologies. In Europe, diesel powertrain sales are dropping precipitously [4]; failing to treat powertrains separately would result in real technical efficiency improvements within powertrains being masked by the shift back to petrol engines.

Regression coefficients for hybrid and electric vehicles are likely to be even more different to conventional engines due to regenerative braking. This reduces the importance of vehicle weight and size on fuel consumption as inertia losses from braking can be recouped by charging the battery. This increases the importance of treating each powertrain separately as performed by *Matas et al.* [13]. However, this subtly changes the questions that can be answered from ‘to what degree have technical efficiency improvements been spent on vehicle attribute increases rather than improving fuel consumption?’ to only answering the question for each powertrain type separately. This means that the effect of shifting sales between powertrains is missing and the rate of TEI can only be quantified for each powertrain rather than for the whole population of vehicles sold.

To address this limitation in past literature, this study proposes a novel decomposition technique to combine the powertrain specific results. This final step allows for changes in average fuel consumption of all new vehicles to be split between three competing factors:

- **Technical Efficiency Improvements (TEI)** within a given powertrain technology (fig. 1A); these are quantified as the incremental reduction in average fuel consumption of vehicles, holding vehicle attributes (such as power and size) constant. TEI are driven by engineering innovation

such as light-weighting, improved combustion, lubrication and aerodynamics and once learnt are unlikely to be lost. TEI are therefore almost always unidirectional [14]; the energy intensity of a vehicle with the same vehicle attributes such as power, size and accessories will tend to improve over time as greater R&D pushes engineering developments to an economic or physical limit [15].

- **Technology Switching (TS)** between different powertrain technologies (fig. 1B); Diesel vehicles offer a more efficient alternative to petrol-engined vehicles of similar size and performance, as do hybrid and electric vehicles [4]. Policies to incentivise sales of one technology over another tend to rely on subsidies (e.g. diesel fuel is taxed less than petrol in many European countries), efficiency labelling schemes and taxes (e.g. registration taxes for electric cars may be lower). Unlike TEI, technology switching is not necessarily unidirectional; in the EU, consumers shifted towards more efficient diesel powertrains between 2000-2014 but have since reverted back to petrol vehicles in light of the 2015 diesel scandals.
- **Vehicle Attribute changes (VA)** within a powertrain technology (fig. 1C); quantified as the increase in energy intensity from changing vehicle attributes such as power, size and number of accessories in vehicles (such as air conditioning, heated seats and infotainment systems).

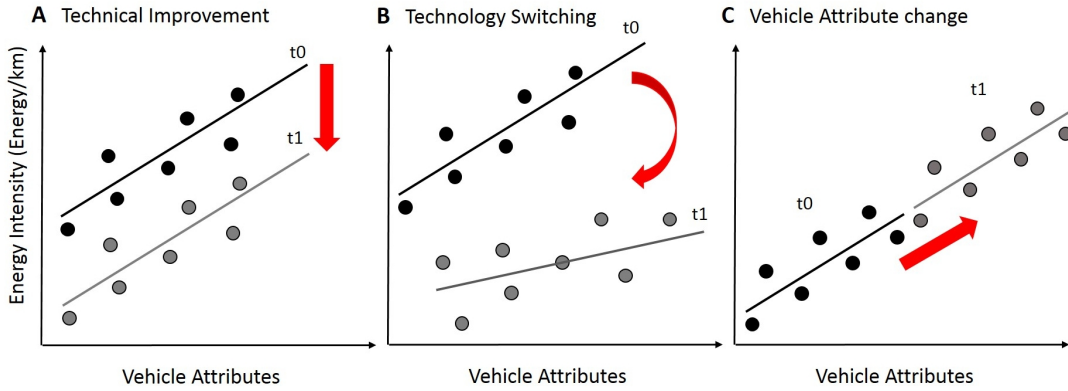


Figure 1: Energy intensity of vehicles (shown as points with trend lines) can change over time (from  $t_0$  to  $t_1$ ) in 3 different ways: Technical Efficiency Improvements within a given technology, TEI (A), Technology Switching, TS (B) and Vehicle Attribute changes, VA (C). Examples of TEI in vehicles include improving vehicle aerodynamics and engine combustion. TS involves changing from e.g. petrol to diesel or hybrid vehicles, VA covers increasing vehicle power/performance and size.

Vehicles having a similar relationship between vehicle attributes (such as power and size) and fuel consumption are assigned to a single ‘technology’. This paper limits itself to separating technology groups by powertrain type (petrol,

diesel and hybrid). In this context, the relationship between vehicle attributes and fuel consumption within a technology are assumed to be constant over time. Any changes in this relationship can only occur via ‘Technology Switching’ (TS) between different technologies.

Research in this sphere is yet to address real-world fuel consumption reported by drivers, which has been found to be considerably higher than manufacturer-quoted, type-approval values. *Tietge et al.* [6] sourced driver reported estimates of vehicle fuel consumption from 1.3 million different vehicles, 15 different publicly available sources and 8 different countries in the EU. The authors found that the average real-world fuel consumption of vehicles available in 2001 was 8% higher than manufacturer reported, type-approval values and by 2017 this gap had risen to 39%. *Stewart et al.* [16] suggest the majority of this growing divergence is due to an increasing degree of exploitation of test ‘flexibilities’ by manufacturers. These include testing vehicles with lower weight and rolling resistance than the equivalent vehicles sold on the road [17]. Other factors explaining the increasing gap include vehicles being sold with a greater number of auxiliaries, which are not included in type-approval testing (air conditioning, infotainment systems), and technologies which have a greater impact on fuel consumption in testing than in real-world conditions such a stop-start ignition. Past authors [11,13] who used type-approval data to quantify technical efficiency improvements (TEI) noted that their findings may be biased due to the increasing divergence with real-world data, but there is yet to be a concerted effort to quantify this effect.

This study quantifies trends in technical efficiency improvements of vehicles in Great Britain between 2001 and 2018 using similar methods to past studies and splitting between different types of powertrains. Building upon past work, this study adds three major novel contributions. The first is including a separate regression for hybrid powertrain vehicles, in addition to the petrol and diesel vehicles studied in past work. Secondly, a new decomposition method is applied to isolate the importance of powertrain technology switching (TS), as well as aggregating technical efficiency improvements (TEI) and vehicle attribute changes (VA) which could previously only be quantified at the powertrain level. Finally, this study accounts for real-world fuel consumption, thereby showing trends of real technical efficiency improvements of British vehicles.

These contributions are relevant to policy-makers as they show the magnitude of real-world energy intensity improvements over the period, as well as the potential efficiency improvements had vehicle attributes remained constant. This allows for insights into the effectiveness of vehicle emissions standards (which became binding in 2008/09 in the EU [18]) at stimulating technical efficiency improvements or limiting vehicle attribute increases.

### 3 Method

This study investigates newly registered vehicles in Great Britain from 2001 to 2018. A dataset is built from several publicly available sources and matched together, details are provided in section 3.1. Next, multivariate regressions are used to isolate annual technical efficiency improvements for each powertrain type, as explained in section 3.2. Finally, annual changes in sales-weighted average fuel consumption are decomposed using log mean divisia index (LMDI) methods into technical efficiency improvements, powertrain switching and vehicle attribute changes, explained in section 3.3.

#### 3.1 Compiling a vehicle database for Great Britain

The dataset used in this paper is created by matching vehicle sales data to other information on vehicle technical characteristics. Vehicle sales data is sourced from the UK Department for Transport (DfT) [19]. This provides annual new registration data at manufacturer and detailed model level (including some trim level characteristics) for vehicles sold in Great Britain between years 2001 and 2018. Using regular expressions, the fuel type, transmission type (Manual/Automatic) and some entries of engine power, turbo-charging and driven-wheels could be extracted for each model. Other technical details for vehicles are limited in this dataset, with no information given for engine capacity, vehicle mass, fuel consumption or dimensions. For years 2010-17, these additional variables are added from the European Environment Agency (EEA) dataset [20], which has the same unique model names as the DfT data allowing for an exact match of each model.

Data from the UK Vehicle Certification Agency (VCA) [21] is used to find the remaining fuel consumption values and engine size of vehicles. This data contains official type-approval (tested) fuel consumption of new vehicles sold in the UK, for each year between 2001 and 2018. Vehicle model names differ in this dataset to the DfT data, therefore ‘fuzzy’ matching algorithms are used to find the best match for each vehicle. Vehicles are screened by manufacturer, sales year fuel type and any other known technical details such as engine capacity, power, hybridisation, turbocharging, drivenwheels and transmission, before being given a score based on the similarity of model names. If the score is above a user-defined threshold the best match is selected, and then manually screened for errors. Further missing information on variables such as weight and engine power is supplemented with publicly available online technical datasets [22], also using the fuzzy matching algorithms and based on the range of years each model variant was sold in. High-level trends are compared to external sources for validation [4, 23].

To present trends in the British vehicle market and ensure the dataset adequately covers all types of vehicles, cars are grouped into one of seven size segments: City Car, Medium Car, Small Sedan, Large Sedan, SUV/MPV (Sports Utility Vehicle/Multiple Passenger Vehicle), Sports and Small SUV. This is

achieved with clustering and classification algorithms, based on vehicle dimensions and body types (further details in the appendix). The fuel consumption of each vehicle is expressed as litres/100km tested over the NEDC combined cycle and converted to gasoline equivalent for all vehicles (one litre of diesel is equal to 36.1/33.5 litres of gasoline based on the respective energy contents of the fuels). Vans and caravans are removed due to limited publicly available fuel consumption data. Registrations of non-new vehicles are also removed.

The ‘New European Drive Cycle’ (NEDC) used for type-approval testing is known to be unrepresentative of real-world driving [5,6]. However, there are still no official government sources of real-world fuel consumption available to use in its place. Real-world fuel consumption data for this study is instead sourced from three online publicly available websites: *Honest John* [24], *Fiches-Auto* [25] and *Spritmonitor* [26], which have also been used in past work investigating the growing divergence between type-approval and real-world fuel consumption [6, 27]. All three websites host user-submitted data and are based in the UK, France and Germany respectively, summary statistics of the real-world fuel consumption data used in this study are shown in table 1.

*Tietge et al.* [6] showed the gap between type-approval fuel consumption and real-world driving conditions was consistent across datasets, despite possible differences in driving habits and weather conditions between countries. The authors also showed the gap to be comparable between data sources from automotive magazines, which tested new vehicles in a more standardised format (controlling for weather conditions etc.) and with national surveys designed to be representative of the population as a whole, assuaging fears of self-selection bias.

	<b>Honest John</b>	<b>Fiches-Auto</b>	<b>Spritmonitor</b> (Sample)
No. Vehicles	5753	3279	1915
No. User Entries	159544	61804	-

Table 1: Summary statistics of real-world data sources. Vehicles are present in multiple sales years. Spritmonitor user entries were not collected as each user submits numerous mileage and fuel readings. Fuel consumption data for vehicles not present on the Honest John and Fiches-Auto websites was sourced from a sample of the full Spritmonitor database.

Fiches-Auto and Honest John data are matched to the vehicle sales data using fuzzy matching scripts by sales year, manufacturer, model, engine capacity and any other available technical information such as power and drivenwheels. For example, a 2015 VW Golf TSI 1.8L in the DfT registration data would be matched with the appropriate car from the Honest John dataset sold between e.g. 2014 and 2017. Any remaining vehicles without real-world fuel consumption estimates were manually entered from Spritmonitor, in particular for early years where Honest John and Fiches-Auto lacked coverage. Overall, 92% of vehicle registrations in each year were given a real-world fuel consumption estimate, this covers over 80% of registrations in each vehicle segment (apart from the sports segment) to ensure a representative sample. Figure 2 shows the real-world fuel

consumption source attributed to each vehicle as a share of registrations each year in the data. For most of the data, vehicles were attributed a match in both the Honest John and the Fiches-Auto data. In these cases the average of the two is taken. In section 4.4, the sensitivity of the results to the choice of real-world fuel consumption data is investigated and further analysis of the uncertainty associated with real-world data is included in the appendix.

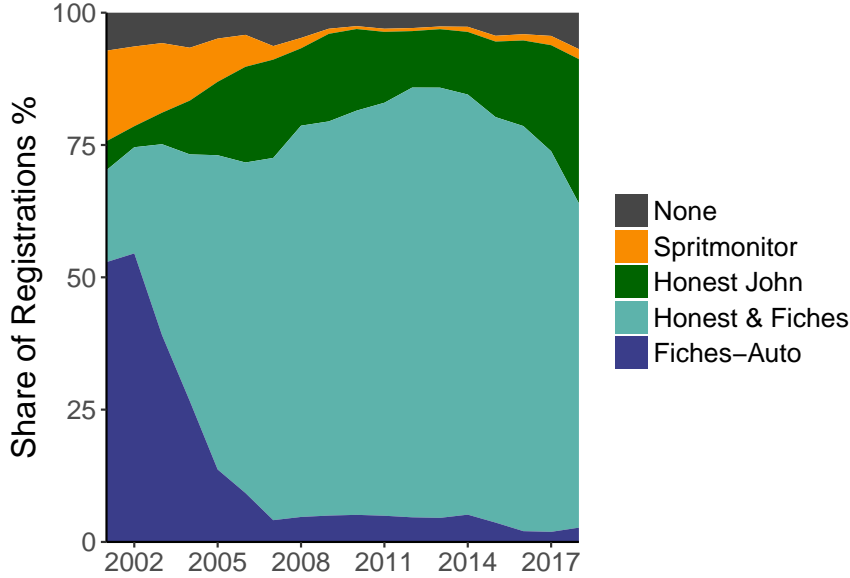


Figure 2: Source of real-world fuel consumption data as a share of new registrations. Data from Honest John and Fiches-Auto are matched to vehicle sales data. For a large share of vehicles, both Honest John and Fiches-Auto data are available (Honest & Fiches). Spritmonitor data is manually entered to bring real-world fuel consumption coverage to over 92% in each year. The remaining vehicles could not be attributed a real-world fuel consumption estimate (None).

### 3.2 Using multivariate regressions to isolate technical improvements

In this study, a regression model similar to previous work [9, 10, 13] is used to disaggregate changes in fuel consumption between changes in vehicle attributes (such as size and power) and technical efficiency improvements (TEI) over time for each powertrain type (equation 1). The effect of each vehicle attribute in the model is determined from the regression coefficients. TEI is determined from the year fixed effects ( $T_t$ , eqn. 1) and is expressed as the change in fuel consumption had vehicle attributes remained constant at 2001 levels. The model is run for petrol, diesel and petrol hybrid vehicles separately as regression coefficients are not the same between each type. Battery electric, plug-in hybrid and other fuel type vehicles are not present in large enough quantities to yield statistically significant results.

The fuel consumption of a vehicle is broadly dictated by powertrain losses (a



function of engine size, power, torque and technology such as turbocharging and fuel type) [28], transmission inefficiencies (a function of number gears, transmission type and drivetrain) and passive system losses [29] from aerodynamic drag (drag coefficient  $C_D$  and frontal area), tyre friction (mass and tyre friction coefficient), inertia losses (mass), as well as driving style, which impacts many of the above.

Data on tyre friction and drag coefficients for each vehicle are not publicly available, nor are they reliable given that manufacturers can take advantage of flexibilities in testing procedures, allowing for drag and rolling resistance coefficients to be improved [30].

The torque and number of gears for each vehicle was not available in the data used in this paper and vehicle weight data could not be associated with a sufficient number of vehicles at detailed model level to attain a representative sample (only 76% of vehicles could be given a weight value). However, this is not an issue. In order to predict real-world fuel consumption, vehicle weight is likely to be associated with a high degree of error. Vehicles are allowed to be type-approved with levels of weight equivalent to the ‘reference’ model. This avoids the weight of accessories such as air conditioning, infotainment systems and electric seats [17]. This means the weight of vehicles on the road can be considerably different to type-approval values (without accounting for the fact certain vehicles may allow for more average passengers and luggage). Vehicle dimensions on the other hand are far less subject to variation between testing and the real world. Since frontal area and length are highly correlated with weight (correlation coefficients 0.72 and 0.81 respectively), the dimensions can also be used as a proxy for weight.

Using engine capacity in the regression captures improvements from a given engine capacity using less fuel. However, technical improvements from engine downsizing, which allow for a reduced engine capacity because more power can be extracted, cannot. For this reason engine rated power is used instead.

The independent variables in each regression model are chosen to capture technical efficiency improvements to the greatest extent given data constraints and with an effort to ensure variables are consistent between type-approval and real-world conditions. The variables used are: rated power, frontal area (the product of width and height), vehicle length as well as whether the vehicle has a manual/automatic transmission, four wheel drive or a turbocharger. Tests for multicollinearity show variance inflation factors are below 2.1 [31]. Breusch-Pagan tests showed heteroskedasticity in the model residuals (meaning the model is less accurate for larger, more powerful vehicles) and therefore standard errors are corrected to ensure heteroskedastic consistency [32].

These regressions quantify the fuel consumption that petrol, diesel and petrol hybrid vehicles could have had if their size, power and other vehicle attributes had remained constant at 2001 levels. This allows for an insight into the technical efficiency improvements in each powertrain type. However, to understand the magnitude of technical efficiency improvements for all vehicles (i.e. not split by powertrain type), decomposition techniques are required; these are explained in

the following section.

### 3.3 Decomposition techniques to isolate the drivers of changing fuel consumption

To better interpret the results of the regressions, a decomposition technique is used to split changes in sales-weighted average fuel consumption of all new vehicles in the UK into three separate components (all expressed in units of fuel consumption, L/100km). These are: technical efficiency improvements within powertrain technologies ( $\Delta\text{TEI}$ ), a structural technology shift in sales between powertrains ( $\Delta\text{TS}$ ) and a change in fuel consumption due to vehicle attribute changes ( $\Delta\text{VA}$ ). By using decomposition techniques, any change in fuel consumption ( $\Delta\text{FC}$ ), can be split into the sum of these three drivers as shown in equation 2.

$$\Delta\text{FC} = \Delta\text{TEI} + \Delta\text{TS} + \Delta\text{VA} \quad (2)$$

Decomposition techniques have been well studied and applied to a variety of fields [33] with various proposed methods to allocate changes between different terms. Methods are favoured if they avoid a residual term (i.e. the left hand side of equation 2 perfectly equals the right) and are symmetrical (i.e. splitting a change in energy intensity from  $I_1$  to  $I_2$  gives the same result as from  $I_2$  to  $I_1$ ). The Log Mean Divisia Index (LMDI) decomposition technique is used in this study as it satisfies these criteria.

Past work [34] used this technique to decompose a change in energy intensity into two terms: changes in energy intensity within subcategories and changes in the volume/importance of subcategories. In this study, the LMDI technique is expanded to include the three drivers in equation 2.

The average fuel consumption in year  $t$  is equal to the product of a technical index, Tech (equal to  $e^{T_t}$  where  $T_t$  are the year fixed effects from equation 1), the share of sales  $S$  of each powertrain  $p$  and the fuel consumption that vehicles would have had in the absence of technical efficiency improvements (the final term in eqn. 3).

$$\text{FC}_t = \sum_p \text{Tech}_{t,p} \times S_{t,p} \times \frac{\text{FC}_{t,p}}{\text{Tech}_{t,p}} \quad (3)$$

By taking the derivative with respect to time  $t$ , discretising for non-continuous data between time  $t$  and  $t + 1$  and rearranging, the following equations can be derived (full derivation is included in the appendix):

$$\Delta\text{TEI} = \text{FC}_t \times \exp\left[\sum_p w_p^* \times \ln\left(\frac{\text{Tech}_{p,t+1}}{\text{Tech}_{p,t}}\right)\right] - \text{FC}_t \quad (4)$$

$$\Delta\text{TS} = \text{FC}_t \times \exp\left[\sum_p w_p^* \times \ln\left(\frac{S_{p,t+1}}{S_{p,t}}\right)\right] - \text{FC}_t \quad (5)$$

$$\Delta VA = FC_t \times \exp \left[ \sum_p w_p^* \times \ln \left( \frac{FC_{p,t+1}/Tech_{p,t+1}}{FC_{p,t}/Tech_{p,t}} \right) \right] - FC_t \quad (6)$$

Where  $w_p^*$  is a weighting function originally proposed by *Vartia* and *Sato* [35, 36] and widely used in other LMDI studies [34, 37]. This decomposition is performed for both type-approval fuel consumption and real-world fuel consumption to compare the magnitude of the drivers.

## 4 Results & Discussion

Disaggregating vehicle fuel consumption into the underlying drivers of change, highlights trends in the British vehicle market and aids in retrospective policy assessment. This section is organised as follows: section 4.1 shows trends in the British vehicle market between 2001 and 2018, section 4.2 presents the results of the multivariate regression models and section 4.3 discusses the results of the decomposition analysis allowing for new insights into the real rates of technical efficiency improvements in vehicles.

### 4.1 Trends in the British Vehicle Market 2001-2018

The market shares of different vehicle size segments in the British market have varied with time as shown in figure 3. In the years before the financial crisis of 2008/9, city and medium cars accounted for over half of the British market, though their market share was dropping steadily in favour of the SUV/MPV segment and small sedans. The shock of the financial crisis caused the total number of registrations to drop sharply between 2008 and 2011. Sales suffered in particular in the larger vehicle segments meaning smaller segments increased as a share of the total. However, since the financial crisis the share of smaller vehicles has again begun to drop, partly due to increased popularity of the small SUV segment. Figure 3 suggests that since 2001, SUV/MPV type vehicles took market share from large sedans, while small SUVs acquired market share from the city and medium car segments.

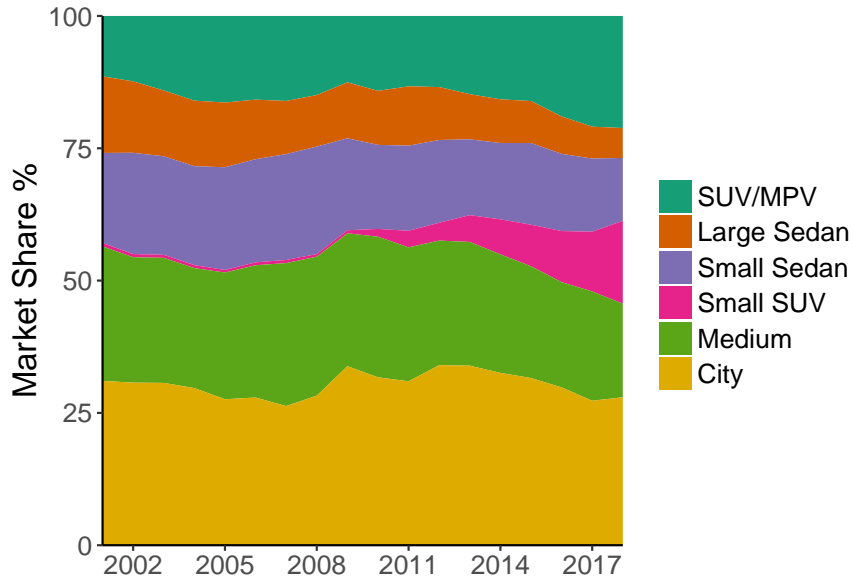


Figure 3: Trends in British vehicle size segment market share 2001-2018.

Figure 4A shows the sales-weighted, type-approval fuel consumption of each segment over the period. Whilst the fuel consumption of all segments has been improving over time, the shifts in sales to the larger segments, which have higher fuel consumption, has reduced the potential for energy efficiency improvements. Figure 4B shows the share of diesel powertrains in each size segment. Diesel powertrains saw a rapid uptake between 2001 and 2012, particularly in the larger size segments. This stimulated improvements in segment average fuel consumption. However, after the diesel-gate scandal in 2015 [38], the share of diesel powertrains across all segments has dropped. The average power and frontal area of all size segments also increased over the period.

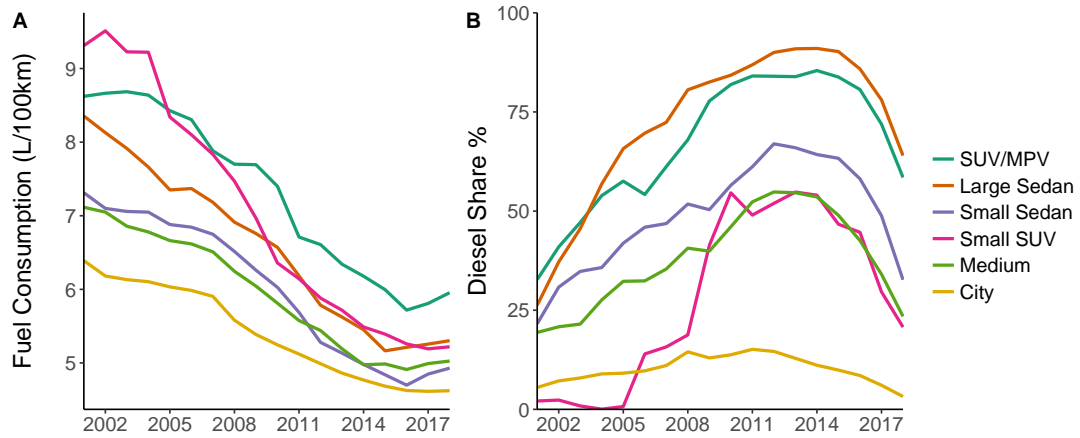


Figure 4: Trends in sales-weighted, type-approval fuel consumption (NEDC) (**A**) and diesel shares (**B**) of British vehicles 2001-2018 by size segment.

## 4.2 Regression Results

The regression models presented in table 2 isolate the effects of vehicle attributes on fuel consumption and thereby leave technical efficiency improvements in the year fixed effects (table A2 in SI). Using these fixed effects, the hypothetical fuel consumption had vehicle attributes in each powertrain remained constant at 2001 levels can be quantified.

It can be seen that regression coefficients vary between different powertrain technologies highlighting that split regression models are indeed needed. Coefficients in the regression using type-approval fuel consumption data are of similar size to past estimates; although true comparisons can only be made between models using the same explanatory variables. The variance explained by the dependent variables ( $R^2$  coefficients) is lower than in past studies [9,10,13]. This is likely due to two factors. The first is that the present study uses a larger number of vehicles than many previous studies, thereby including the full spectrum of vehicle designs; vehicles with high residual fuel consumption not explained by the model are found to have atypical designs (e.g. the Land Rover Defender, which has unusually low power for its size). The second is that the year fixed effects are based on vehicle sales year (like that of *Matas et al.*) rather than vehicle model year (like that of *Knittel* and *Mackenzie & Heywood*). The year fixed effects for petrol hybrids are only statistically significant after 2008 and after 2013 for type-approval and real-world fuel consumption respectively.

The regressions for real-world fuel consumption of petrol and diesel vehicles have a lower  $R^2$  coefficient than those using type-approval data, due to the inherent noise in real-world estimates from a variety of factors that affect fuel consumption outside of laboratory testing conditions, such as driving style and weather (see [39] for a comprehensive breakdown). The models are nonetheless able to give an insight into the magnitude of technical efficiency improvements over the period studied.

<b>Type Approval</b>	<b>Petrol</b>	<b>Diesel</b>	<b>Hybrid</b>
(Intercept)	-6.915 (0.11)***	-14.912 (0.127)***	-3.982 (0.84)***
log(kw)	0.401 (0.002)***	0.289 (0.003)***	0.406 (0.009)***
log(Area)	0.425 (0.008)***	0.977 (0.008)***	0.271 (0.058)***
log(Length)	0.12 (0.008)***	0.142 (0.012)***	
Manual	-0.021 (0.001)***	-0.067 (0.001)***	
AWD	0.033 (0.002)***	0.066 (0.002)***	0.119 (0.031)***
Turbo	-0.077 (0.001)***		
R <sup>2</sup>	0.841	0.771	0.858
R <sup>2</sup> adj	0.841	0.771	0.854
Observations	49034	36313	717
<b>Real World</b>	<b>Petrol</b>	<b>Diesel</b>	<b>Hybrid</b>
(Intercept)	-8.808 (0.105)***	-13.893 (0.107)***	-9.51 (0.749)***
log(kw)	0.334 (0.002)***	0.34 (0.002)***	0.368 (0.008)***
log(Area)	0.589 (0.008)***	0.96 (0.007)***	0.66 (0.052)***
log(Length)	0.093 (0.008)***	0.019 (0.01)*	
Turbo	-0.031 (0.001)***		
R <sup>2</sup>	0.753	0.759	0.885
R <sup>2</sup> adj	0.753	0.759	0.882
Observations	47212	36219	733

Table 2: Regression results using equation 1 for Petrol, Diesel and petrol Hybrid vehicles separately. Dependent variable is the natural log of type-approval fuel consumption (litres of gasoline equivalent/100km), standard errors for each coefficient are included in parentheses. Independent variables are vehicle power (kw), frontal area (m<sup>2</sup>), vehicle length (m), transmission type (Manual/Automatic), four wheel drive (AWD) and turbo-charging (Turbo). Each model also includes year fixed effects which are presented in the appendices. Statistical significance of t-tests: \* p<0.05, \*\* p<0.01, \*\*\* p<0.001

The regressions isolate year-on-year technical efficiency improvements which can be used to quantify the hypothetical fuel consumption that vehicles could have attained had vehicle attributes remained constant at 2001 levels (table 3). This is shown in figure 5 for each type of powertrain and both type-approval and real-world data. Comparing this hypothetical case to the trends in sales-weighted fuel consumption shows the amount that technical efficiency improvements were offset by increases in size and power.

Over the period studied, the gap between type-approval and real-world fuel consumption grew for all three powertrains investigated. In 2001, sales-weighted real-world fuel consumption for petrol, diesel and petrol hybrid vehicles was 4%, 4% and 5% higher than type-approval fuel consumption respectively. By 2018 this gap grew to 34%, 36% and 35% higher. These results are similar to the non-sales-weighted results presented by *Tietge et al.* [6] for the EU.

	2001				2018			
	Diesel	HEV	Petrol	Total	Diesel	HEV	Petrol	Total
Power (kw)	75	53	74	74	116	84	97	102.8
Area (m <sup>2</sup> )	2.6	2.5	2.5	2.5	2.9	2.7	2.7	2.8
Length (m)	4.4	4.3	4.1	4.2	4.6	4.4	4.2	4.4
TA FC (L/100km)	6.5	5.1	7.5	7.3	5.1	3.9	5.3	5.2
RW FC (L/100km)	6.8	5.4	7.8	7.6	6.9	5.2	7.0	7.0
Share (%)	17%	0%	83%	100%	28%	4%	69%	100%
Registrations ( $\times 10^3$ )	436	0.6	2066	2502	569	73.1	1418	2060

Table 3: Sales-weighted average statistics of vehicles split by powertrain type (Petrol, Diesel and Petrol Hybrid vehicles). Engine power (kw), frontal area (m<sup>2</sup>), vehicle length (m), type-approval fuel consumption (TA FC), real-world fuel consumption (RW TC) and percentage share and number of registrations. All fuel consumption in litres of gasoline equivalent per 100km.

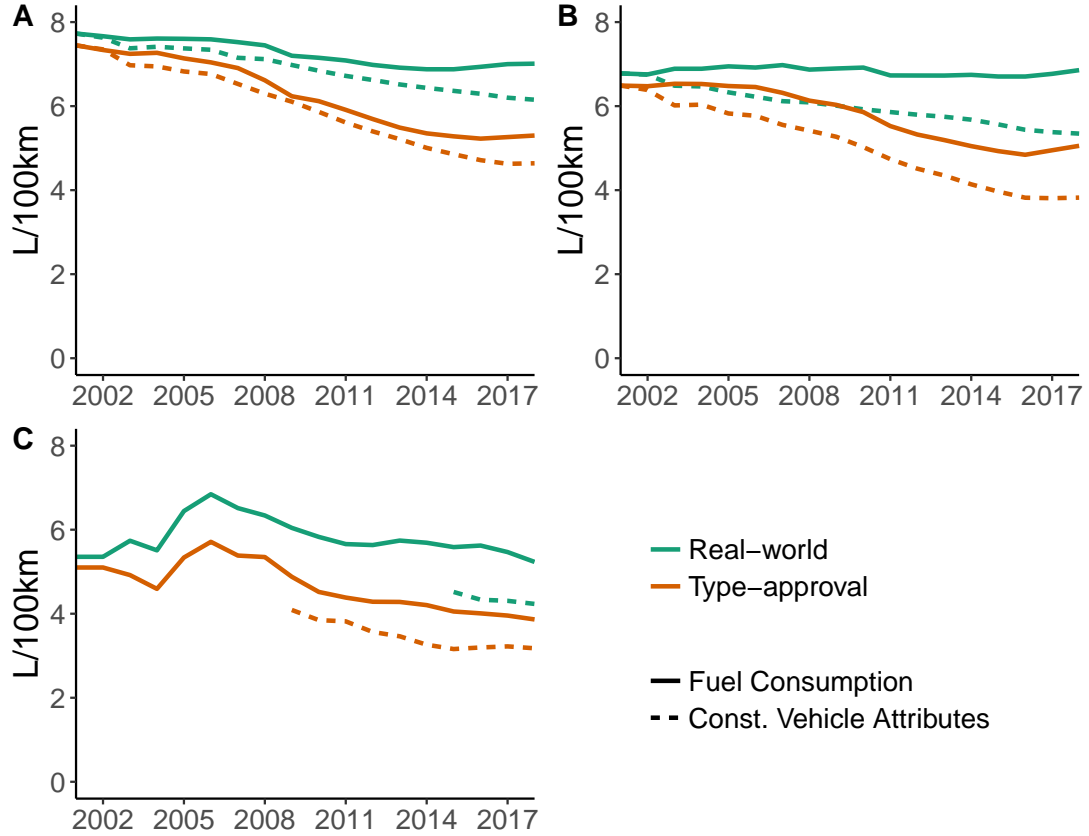


Figure 5: Changes in sales-weighted type-approval and real-world fuel consumption (FC) between 2001 and 2018 (solid lines) for **A**= Petrol vehicles, **B**= Diesel vehicles, **C**= Petrol Hybrid vehicles. Also shown is the hypothetical fuel consumption vehicles could have attained had vehicle power and size and other vehicle attributes remained constant at 2001 levels (dashed). Hypothetical fuel consumption for Petrol Hybrid vehicles is only shown where year fixed effects are statistically significant at the  $p < 0.05$  level.

The real-world fuel consumption of petrol cars improved by just 0.8 L/100km over the time period; had TEI been maximised, fuel consumption could have improved by 1.6 L/100km, instead size and power increases (table 3) offset 54% of this potential. The real-world fuel consumption of diesel vehicles increased from 2001 by 0.1 L/100km, TEI could have reduced fuel consumption by 1.4 L/100km but this was more than offset by vehicle attribute increases.

The fuel consumption of hybrid vehicles increased sharply in 2005/06 as large hybrid powertrain SUVs entered the market which had previously only featured small sedan type vehicles such as the Toyota Prius. Had vehicles remained at the size and power of a 2001 Toyota Prius, the average real-world fuel consumption could have been 4.2 L/100km instead of the observed 5.2 L/100km average.

### 4.3 Decomposition Results

This section presents the results of the LMDI decomposition which splits changes in British average fuel consumption into the contributions from TEI, TS and VA using the powertrain specific results shown in figure 5. Figure 6A shows type-approval fuel consumption in 2001 and 2018 and the magnitude of TEI, TS and VA over the period. Between 2001 and 2018, technical efficiency improvements contributed to reducing type-approval fuel consumption by 3.0 L/100km. Switching from petrol to diesel and hybrid vehicles improved fuel consumption by 0.2 L/100km. The relatively meagre gains from sales shifts in powertrains are due to two factors. The first is that the average fuel consumption of petrol and diesel vehicles was relatively similar, particularly in later years. The second is that hybrid vehicles had a low effect due to their low market share which was just 4% of sales in 2018.

If vehicle attributes had remained constant at 2001 levels in each powertrain (table 3), type-approval fuel consumption could have improved from 7.3 L/100km in 2001 to 4.1 L/100km in 2018. Instead, increasing vehicle size and power led to a 1.1 L/100km deterioration in type-approval fuel consumption.

Over the 18 year period, real-world average fuel consumption improved by just 0.65 L/100km (fig.6B). The effects of the technology switching has been similar between the real-world and type-approval cases, as have the effects of vehicle attributes changes. Real-world technical efficiency improvements on the other hand were just 1.6 L/100km meaning that 60% of TEI has been offset by increasing vehicle attributes.



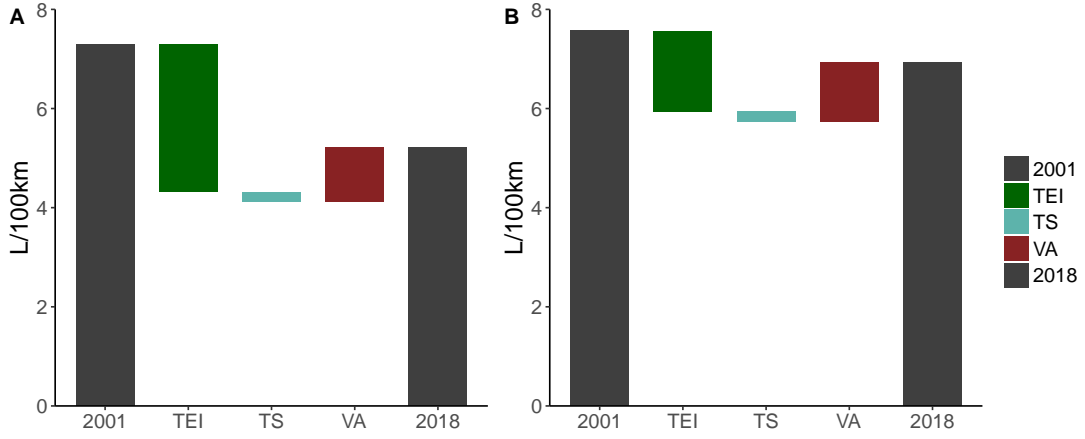


Figure 6: Decomposition of changes in British vehicle fuel consumption between 2001 and 2018, **A** = Type-approval, **B**= Real-world. TEI= Technical efficiency improvements within a powertrain technology (petrol, diesel and hybrid), TS= Technology switching between different powertrain technologies and VA=Vehicle Attribute changes in power and vehicle size. Hybrid vehicles are only included when year fixed effects are statistically significant at  $p < 0.05$ .

Figure 7A shows yearly trends in sales-weighted type-approval and real-world fuel consumption. The rate of improvement in type-approval fuel consumption increased after 2008-09 coinciding with mandatory EU emissions standards suggesting they were effective at improving vehicle fuel consumption. However, real-world fuel consumption trends offer a contrasting picture, with a limited improvement between 2001 and 2018. Between 2016-18 the average fuel consumption of British vehicles deteriorated, both for type-approval and real-world. Disaggregating these changes in fuel consumption into the underlying drivers can help to explain these trends.

Figure 7B shows the change in fuel consumption (FC) since 2001 and the cumulative change in TEI, TS and VA for both real-world and type-approval data (also shown in table A3). The sum of the contributions of TEI, TS and VA in any year in figure 7B is equal to the change in FC (see eqn. 2). Vehicle attribute increases continue to offset technical efficiency improvements, and at an increasing rate in later years.

Examining the rates of technical efficiency improvements calculated using type-approval data reveals two findings. The first is that TEI accelerates after the introduction of EU emissions standards in 2008/09 as reported by *Klier & Linn* [12] for vehicles in the EU. However, this trend is less significant for real-world data. This suggests the introduction of the EU emissions standards increased the use of test flexibilities rather than driving real increases in the rate of TEI. Secondly, the rates of TEI using type-approval data slow in 2017/18, but this effect is again not evident with real-world data. This could be due to manufacturers reducing the exploitation of test flexibilities in order to comply with the incoming World Harmonised Light Vehicle Test (WLTP) cycle which will become mandatory from 2019 in the UK.

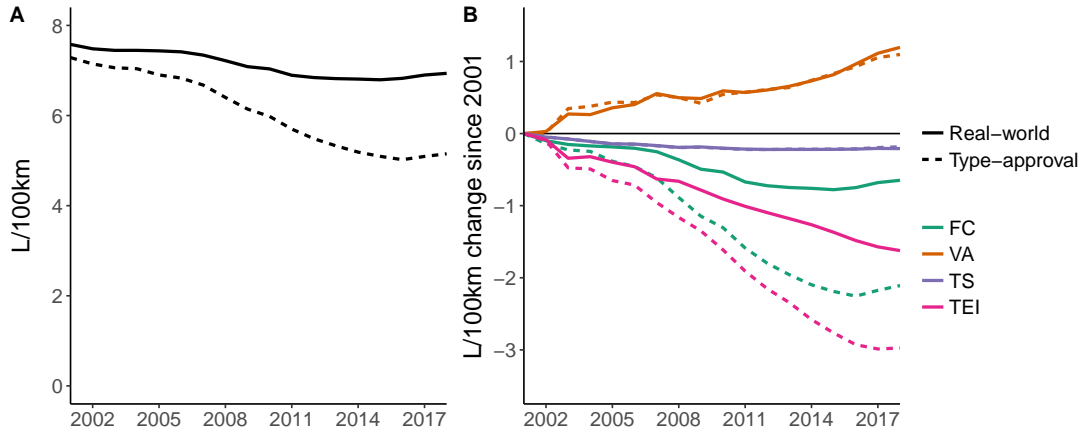


Figure 7: **A**= Trends type-approval fuel consumption (NEDC) and reported real-world fuel consumption. Both are sales-weighted and converted to litres of gasoline equivalent/100km. **B**= Trends in Technical efficiency improvements (TEI), Technology switching (TS), vehicle attribute changes (VA) and sales-weighted fuel consumption (FC) split by type-approval and real-world fuel consumption. Results are expressed as the cumulative change since year 2001.

#### 4.4 Sensitivity of data source

Over half of vehicles were attributed a real-world fuel consumption estimate from both the Honest John and Fiches-Auto datasets (see fig. 2). For these vehicles, there is a choice between preferring British data, French data or using the average of both (as performed in the preceding sections). This section investigates the sensitivity of this choice.

Figure 8A shows the sales-weighted percentage difference between real-world and type approval fuel consumption for all vehicles, split by preference towards Honest John or Fiches-Auto data for vehicles with multiple matches. Between 2001 and 2008 both datasets show similar levels of divergence. However, in later years the divergence grows more rapidly when using the French dataset. The data limits the analysis of this difference but reasons could include the increasing penetration of air conditioning and its likely higher use in France.

Figure 8B shows how the choice of real-world fuel consumption data for vehicles with multiple matches influences TEI following the decomposition analysis for all vehicles. The rates of improvement (in L/100km per year) of fuel consumption and TEI are also detailed in table 4 and averaged over one of three periods for ease of interpretation: 2001-2008 before the introduction of EU CO<sub>2</sub> emissions standards, 2008-2016 the period following the introduction of the standard and 2016-2018, the period following diesel-gate in which the average fuel consumption of British vehicles worsened. A preference of British data (Honest John) means the rates of improvement in both fuel consumption (FC) and technical efficiency improvements (TEI) increase slightly post 2008. However, the main conclusion remains that real world rates of TEI remain well below those calculated using type approval data and the introduction of EU CO<sub>2</sub>

emission standards had a limited effect at increasing rates of real world TEI.

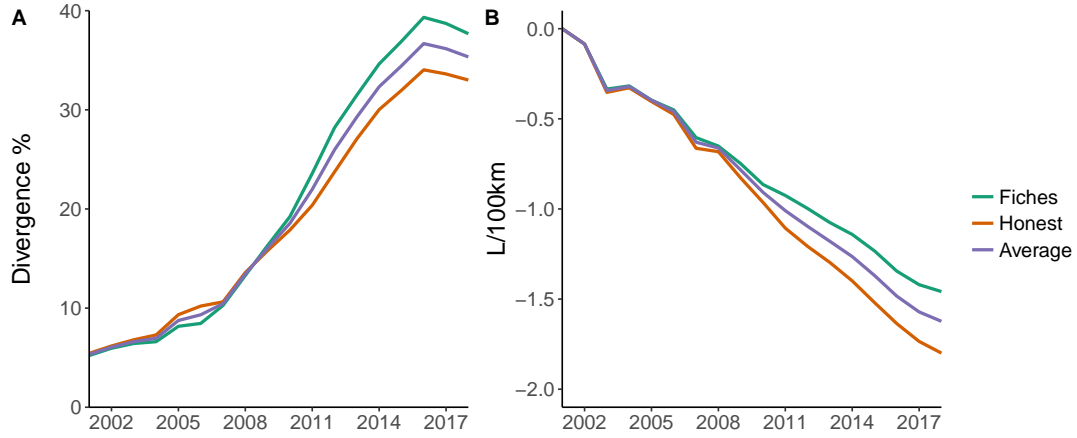


Figure 8: **A**= Percentage Divergence between real-world fuel consumption and type approval data and **B**=TEI using real-world data for all vehicles, split by preference towards Honest John data, Fiches-Auto data and the average of both for vehicles with multiple matches.

Source		FC			TEI		
		2001-08	2008-16	2016-18	2001-08	2008-16	2016-18
TA		-0.13	-0.17	0.07	-0.17	-0.22	-0.02
RW	Fiches-Auto	-0.05	-0.03	0.05	-0.09	-0.09	-0.05
	Honest John	-0.05	-0.07	0.06	-0.1	-0.12	-0.07
	Average	-0.05	-0.05	0.05	-0.09	-0.1	-0.06

Table 4: Comparison of average improvement rates (L/100km per year) in average fuel consumption (FC) and Technical Efficiency Improvements (TEI) using both type approval (TA) and real-world (RW) data. Real-world data is split by a preference toward using Fiches-Auto data, Honest John data and the average of both sources.

## 4.5 Limitations

The decomposition analysis isolates the hypothetical fuel consumption that vehicles could have attained if their vehicle attributes *in each powertrain* remained at 2001 levels (table 3). It also isolates the fuel consumption lost to increases in vehicle attributes in each powertrain. However, when two powertrains have different average vehicle attributes, then technology switching also entails a measure of VA. Switching from an average petrol car to an average diesel car involves an improvement in engine efficiency but also a slight increase in average vehicle size and power. This means the magnitudes of TS and VA are likely to be conservative. This cannot be captured using the decomposition used in this paper and merits further consideration.

Next, users of the real-world fuel consumption websites likely upload information on vehicles which have a range of ages. A model year 2017 vehicle on the websites is likely to have been relatively new when the user uploaded their fuel consumption estimates, this may not be the same for a 2001 year vehicle. This raises two sources of potential bias: 1. driver type bias; an older vehicle could be owned by a different type of driver who drives their vehicle in a different way (e.g. more urban vs. rural driving) 2. vehicle age bias; if the vehicle is older and has higher cumulative mileage, it could have different technical characteristics compared to when it was new (e.g. engine wear and tear).

The real-world fuel consumption data for this paper reports the average fuel consumption reported by all users for each model of vehicle. The data did not include individual user entries with the age of the vehicle at the time it was reported meaning vehicle age cannot be explicitly controlled for. When reporting data to all three websites, users select whether they were driving in mostly urban environments, mostly rural or mixed. The data sourced for this paper only used mixed data. This will reduce potential driver type bias, though some may remain and is an inevitable product of this type of data, which benefits from large samples but lacks standardised test conditions. It is possible that drivers of older vehicles also have a different average driving style to those of newer vehicles (e.g. more aggressive or more eco-driving). *Tietge et al.* [40] investigate this and show users of the Spritmonitor database report relatively constant driving styles. There is no reason to believe this would be different for the other two data sources used in this paper.

Regarding vehicle age bias, there is relatively little literature reporting the effect of cumulative vehicle mileage or age on vehicle fuel economy. The only paper we are aware of is *Greene et al.* [41] in which the authors investigate real-world fuel economy of vehicles as they age in the USA. The authors show that the fuel economy of gasoline vehicles improves by approximately 2% in a vehicle's first 20,000 miles (which is around 2 years of driving) before remaining within 1% of a saturation value. Interestingly, the fuel economy of hybrid vehicles is found to gradually worsen over time (by 1% after 20,000 miles and 3% after 150,000 miles), potentially due to battery degradation. If these findings were to hold for British vehicles, it could introduce vehicle age bias for hybrid vehicles in particular. However, given that hybrid vehicles make up a negligible share of vehicle sales in the UK (4% in 2018) and the fuel consumption of gasoline vehicles stabilises after approximately 2 years, vehicle age bias is unlikely to affect the rates of TEI reported in this paper or the main finding regarding the response to EU CO<sub>2</sub> standards in 2008/09. Quantifying the impact of cumulative mileage and age on vehicles in Europe, and diesel vehicles in particular, is nonetheless an interesting avenue for future work.

## 5 Conclusions and Policy Implications

Ensuring that fuel economy standards are effective at driving real efficiency improvements is essential to reduce CO<sub>2</sub> emissions from vehicles. The new framework presented in this paper allows for changes in vehicle fuel consumption to be split into three underlying drivers: incremental technical efficiency improvements, market shifts between powertrain types and the effect of increasing vehicle attributes such as power and size. By quantifying these effects using driver-reported, real-world fuel consumption data, the success of policies aiming to stimulate efficiency improvements can be evaluated.

Between 2001 and 2018 real technical efficiency improvements could have reduced fuel consumption by 1.6 L/100km, instead 60% of this potential was offset by increasing size and power of vehicles. The introduction of EU fuel economy standards in 2008/09 had little effect on the rate of real technical efficiency improvements in British vehicles. These results suggest that instead of adopting technical improvements at a higher rate or limiting the size and power of vehicles, manufacturers met emissions standards by increasing the divergence between laboratory tests and real-world fuel consumption.

The real-world fuel consumption of new British vehicles deteriorated in 2017 and 2018. Three main policy strategies are suggested to avoid this continuing. The first is to increase the rates of technical efficiency improvements in powertrains. This can be stimulated by ensuring fuel economy standards are based on a drive-cycle that is representative of real-world driving, to avoid the exploitation of test flexibilities. The WLTP test is expected to be a step in the right direction compared with the outgoing NEDC, but *Stewart et al.* [16] suggest the gap between type-approval and real-world driving under WLTP will increase over time.

The second strategy is to reduce vehicle size and power by further increasing registration taxes on larger vehicles. This can also be aided by making tests more representative of real-world driving. *Tietge et al.* [6] found that sedans have a higher gap between type-approval and real-world fuel consumption than smaller cars. Making tests more representative of real-world fuel consumption would therefore push larger vehicles into higher registration tax bands (this is particularly the case for small sedans in fig. A2 in the SI). The final strategy to improve fuel consumption is to increase technology switching by further stimulating the adoption of hybrid and electrified vehicles, for example, through a bonus-malus subsidy system.

Future work could extend this analysis to countries such as Japan and the USA, which do not use the NEDC cycle for type-approval testing procedures, to investigate whether the rate of real-world technical efficiency improvements increased in response to fuel economy standards. This analysis could also include electric and plug-in hybrid vehicles as more data becomes available.

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## References

- [1] International Energy Agency, “Energy Technology Perspectives,” *IEA*, 2017.
- [2] International Energy Agency (IEA), “Energy Efficiency Market Report,” *Market Report Series*, 2018.
- [3] International Energy Agency, *World Energy Outlook 2018*. World Energy Outlook, OECD, nov 2018.
- [4] IEA and ICCT, “Fuel Economy in Major Car Markets: Technology and Policy Drivers 2005-2017,” *GFEI - Global Fuel Economy Initiative Working Paper 19*, 2019.
- [5] L. Ntziachristos, G. Mellios, D. Tsokolis, M. Keller, S. Hausberger, N. E. Ligterink, and P. Dilara, “In-use vs. type-approval fuel consumption of current passenger cars in Europe,” *Energy Policy*, vol. 67, no. 2014, pp. 403–411, 2014.
- [6] U. Tietge, S. Díaz, P. Mock, A. Bandivadekar, J. Dornoff, and N. Ligterink, “From Laboratory to Road 2018 Update,” *ICCT White Paper*, no. January, 2019.
- [7] S. Sorrell, “Fuel efficiency in the UK vehicle stock,” *Energy Policy*, vol. 20, no. 8, pp. 766–780, 1992.
- [8] T. H. Kwon, “The determinants of the changes in car fuel efficiency in Great Britain (1978-2000),” *Energy Policy*, vol. 34, no. 15, pp. 2405–2412, 2006.
- [9] B. C. R. Knittel, “Automobiles on Steroids : Product Attribute Trade-Offs and Technological Progress in the Automobile Sector,” *The American Economic Review*, vol. 101, no. 7, pp. 3368–3399, 2011.
- [10] D. MacKenzie and J. B. Heywood, “Quantifying efficiency technology improvements in U.S. cars from 1975-2009,” *Applied Energy*, vol. 157, no. 2015, pp. 918–928, 2015.
- [11] K. Hu and Y. Chen, “Technological growth of fuel efficiency in european automobile market 1975–2015,” *Energy Policy*, vol. 98, pp. 142–148, 2016.

- [12] T. Klier and J. Linn, “The effect of vehicle fuel economy standards on technology adoption,” *Journal of Public Economics*, vol. 133, pp. 41–63, 2016.
- [13] A. Matas, J. L. Raymond, and A. Dominguez, “Changes in fuel economy: An analysis of the Spanish car market,” *Transportation Research Part D: Transport and Environment*, vol. 55, pp. 175–201, 2017.
- [14] R. Goerlich and F. Wirl, “Interdependencies between transport fuel demand, efficiency and quality: An application to Austria,” *Energy Policy*, vol. 41, pp. 47–58, 2012.
- [15] J. M. Cullen, J. M. Allwood, and E. H. Borgstein, “Reducing Energy Demand: What Are the Practical Limits?,” *Environmental Science & Technology*, vol. 45, no. 4, pp. 1711–1718, 2011.
- [16] U. Stewart, A., Hope-Morley, A., Mock, P., Tietge, “Quantifying the impact of real-world driving on total CO2 emissions from UK cars and vans,” *Final Report for the Committee on Climate Change*, pp. 1–52, 2015.
- [17] G. Kadijk, M. Verbeek, R. Smokers, J. Spreen, A. Patuleia, M. Van, R. Aea, J. Norris, R. A. Johnson, S. O’Brien, S. Wrigley, J. Pagnac, M. Seban, and D. Buttigieg, “Supporting Analysis on Test Cycle and Technology Deployment for Reviews of Light Duty Vehicle CO 2 Regulations,” *TNO*, 2012.
- [18] EU and European Commission, “Regulation (EC) No. 443/2009 of the European Parliament and of the Council of 23 April 2009 Setting Emission Performance Standards for New Passenger Cars as Part of the Community’s Integrated Approach to Reduce CO2 Emissions from Light-duty Vehicles,” *Official Journal of the European Union*, pp. 1–15, 2009.
- [19] UK Department for Transport, “Table VEH0160: Vehicles registered for the first time by make and model,” *Vehicles Statistics*, 2018.
- [20] EEA, “Monitoring of CO2 emissions from passenger cars – Regulation (EC) No 443/2009,” 2018.
- [21] UK Vehicle Certification Agency, “Car fuel and emissions information,” 2018.
- [22] Z. McGregor, “www.carfolio.com,” 2017.
- [23] SMMT, “New Car CO2 Report 2018,” *Society of Motor Manufacturers and Traders*, 2018.
- [24] D. Harrison and D. Powell, “www.honestjohn.co.uk/real-mpg/,” 2019.
- [25] E. Naudot, “http://www.fiches-auto.fr/essais-tests/,” 2018.
- [26] T. Fischl, “https://www.spritmonitor.de/en/,” 2019.

- [27] U. Tietge, P. Mock, V. Franco, and N. Zacharof, “From laboratory to road: Modeling the divergence between official and real-world fuel consumption and CO<sub>2</sub> emission values in the German passenger car market for the years 2001–2014,” *Energy Policy*, vol. 103, no. May 2016, pp. 212–222, 2017.
- [28] G. Sovran and D. Blaser, “A Contribution to Understanding Automotive Fuel Economy and its Limits,” *SAE International 2003-01-2070*, 2003.
- [29] J. M. Cullen and J. M. Allwood, “The efficient use of energy: Tracing the global flow of energy from fuel to service,” *Energy Policy*, vol. 38, no. 1, pp. 75–81, 2010.
- [30] J. Kühlwein, “The impact of official versus real-world road loads on CO<sub>2</sub> emissions and fuel consumption of European passenger cars,” *ICCT White Paper*, no. May, pp. 1–54, 2016.
- [31] D. G. Kleinbaum, *Applied regression analysis and other multivariable methods*. Duxbury, 3rd ed., 1998.
- [32] J. S. Long and L. H. Ervin, “Using Heteroscedasticity Consistent Standard Errors in the Linear Regression Model,” *The American Statistician*, vol. 54, no. 3, pp. 217–224, 2000.
- [33] F. L. Liu and B. W. Ang, “Eight methods for decomposing the aggregate energy-intensity of industry,” *Applied Energy*, vol. 76, pp. 15–23, 2003.
- [34] B. Ang and K.-H. Choi, “Decomposition of Aggregate Energy and Gas Emission Intensities for Industry: A Refined Divisia Index Method,” *The Energy Journal*, vol. 18, no. 3, pp. 59–73, 1997.
- [35] Y. O. Vartia, “Ideal Log-Change Index Numbers,” *Scandinavian Journal of Statistics*, vol. 3, no. 3, pp. 121–126, 1976.
- [36] K. Sato, “The Ideal Log-Change Index Number,” *The Review of Economics and Statistics*, vol. 58, no. 2, pp. 223–228, 1976.
- [37] B. W. Ang, “LMDI decomposition approach : A guide for implementation,” *Energy Policy*, vol. 86, pp. 233–238, 2015.
- [38] US EPA, “Notice of Violation on Clean Air Act to Volkswagen AG Sep 18,” 2015.
- [39] G. Fontaras, N. G. Zacharof, and B. Ciuffo, “Fuel consumption and CO<sub>2</sub> emissions from passenger cars in Europe – Laboratory versus real-world emissions,” *Progress in Energy and Combustion Science*, vol. 60, pp. 97–131, 2017.
- [40] U. Tietge, P. Mock, J. German, A. Bandivadekar, and N. Ligterink, “From Laboratory To Road a 2017 Update of Official and Real-World Cars in Europe,” *ICCT White Paper*, no. November, 2017.



- [41] D. L. Greene, J. Liu, A. J. Khattak, B. Wali, J. L. Hopson, and R. Goeltz, “How does on-road fuel economy vary with vehicle cumulative mileage and daily use?,” *Transportation Research Part D: Transport and Environment*, vol. 55, pp. 142–161, 2017.